Change in Global Temperature: A Statistical Analysis

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ABSTRACT

This paper investigates several issues relating to global climatic change using statistical techniques that impose minimal restrictions on the data. The main findings are as follows: 1) The global temperature increase since the last century is a systematic development. 2) Short-term variations in temperature do not have long-lasting effects on the final realizations of the series; over time, stochastic perturbations dissipate and temperature reverts to trend. 3) Multivariate tests for causality demonstrate that atmospheric CO_2 is a significant forcing factor. The implied change in temperature with respect to a doubling of atmospheric CO_2 lies in a range of 2.17° to 2.57°C, with a mean value of 2.34°C. The contributions of solar irradiance and volcanic loading are much smaller. 4) In a multivariate system, shocks to forcing factors generate stochastic cycles in temperature comparable to the results from unforced simulations of climatological models. 5) Extrapolation of regression equations predict changes in global temperature that are marginally lower than the results from climatological simulation models.

1. Introduction

Most analysis of temperature change has been conducted using climatological simulation models, which impose a well-defined theoretical structure on the data. In such models, the magnitudes of interactions between temperature and exogenous forcing factors are imposed on the basis of relationships known from thermodynamics or otherwise established in the laboratory.[1] An alternative approach is to use statistical techniques, which place comparatively few restrictions on the data. Rather than impose causal relationships known from physics, causality is here estimated directly from historical time series. Models of this type are inexpensive to build and simulate; however, they necessarily sacrifice the detail that is possible using large-scale simulation models.

This paper has the following objectives:

1) to determine whether the increase in temperature since the nineteenth century has been systematic or might simply be the result of random fluctuations.

2) to measure the persistence of stochastic shocks to temperature, that is, whether perturbations eventually dissipate, or are permanently reflected in the level of temperature.

3) to estimate the magnitude of causal relationships between temperature and exogenous forcing factors.

4) Using these regressions, to compute forecasts for temperature and compare the extent to which predictions derived from climatological models are consistent with the results obtained from statistical methods.[2]

Section 2 describes the temperature data. Sections 3 and 4 test for degree of integration and trend reversion. Sections 5–7 conduct a multivariate causal analysis. Section 8 computes the forecasts.

2. The temperature data

There has been some debate as to whether climatic forecasts should be based on the global mean temperature, or whether a more disaggregated approach should be used. Hansen et al. (1988) argue that the global-mean temperature minimizes the signal-to-noise ratio in the data. On the other hand, Barnett and Wigley

[1] For more on the properties of climatological simulation models and their implications for future climatic change, see Gates (1985) and Wang et al. (1986). With respect to the accuracy of simulation models for predicting global temperature specifically, see Hansen et al. (1988).

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[2] Of the procedures used here, atheoretical approaches have been essayed on prior occasions, primarily in the context of estimating the degree of persistence in temperature fluctuations (Karl 1988; Karl and Riebsame 1984; Mandelbrot and Wallis 1969). Regression of temperature on forcing mechanisms has also been used on prior occasions, but there is still little consensus as to model specification (Gilliland 1982; Schonwiese 1991).

(1990) have suggested that there may be important latitudinal differences in observed temperature variation, arguing for greater disaggregation (see also Barnett and Schlesinger 1987). This is in essence a cointegration issue. If temperatures at different latitudes are cointegrated (share a common stochastic trend), they will on average move together over time, although they may drift apart over shorter term horizons (see Engle and Granger 1987). In this eventuality, the global mean will constitute an appropriate indicator. A subsequent study will investigate the issue of common stochastic trends. For the time being, however, this analysis will focus on the global-mean temperature.

Several sets of data are available for the global temperature anomaly (denoted ΔT) from the mid-nineteenth century onward. Two series compiled for the Climatic Research Unit at the University of East Anglia include land and sea temperatures, and land-based temperatures only (Jones 1988a,b, 1990). A somewhat different series, used in IPCC (1990), is described in Folland et al. (1990). These three datasets are available from 1854, 1858, and 1856–1990, respectively; the anomalies are in reference to the 1950–79 mean (P. Jones, personal communication 1991). A fourth set is an unpublished series for the period 1854–1986 computed by the National Center for Atmospheric Research (NCAR). A final set based primarily on land temperatures is compiled in Hansen and Lebedeff (1987, 1989), but begins only in 1880; because of the shorter interval, it is not used here. In using all four datasets, it is not maintained that any of them are preferable in the sense of yielding more accurate findings. Rather, estimating the tests for the four sets makes it possible to obtain a parametric range of results. In all the datasets, the frequency is annual, eliminating any seasonal component. Temperature is measured in degrees centigrade. The use of the Celsius scale is essentially arbitrary. If the data is converted to kelvins, the elasticities of response to forcing differ because the scale of the data is changed by an additive constant; however, the forecast results for global temperature are unaffected.

The temperature anomaly is of course defined as the deviation from the mean. This data is difficult to work with for several reasons. First, if the temperature data is nonstationary, the mean, variance, and covariance will be time dependent. Second, the causal relationships between temperature and exogenous forcing factors may prove to be nonlinear, implying model specifications in which the coefficients enter as exponents. Equations of this type can be linearized by taking logarithms. The anomaly cannot be logged because it incorporates negative values, but when the base mean temperature is added in, logs can be taken. The preferred measure is therefore the log of temperature ($\ln T_t$). The base mean of 14.22°C was calculated by NCAR from the Northern and Southern Hemisphere climatologies of Crutcher and Maserve (1970) and Taljaard et al. (1969). It is acknowledged that there is some uncertainty with respect to the base mean temperature, due to factors such as differences in elevation and lack of data for certain regions; however, the use of logarithmic data significantly improves the reliability of the tests conducted here. Further, uncertainty with respect to the mean value will not affect the forecasts for the anomaly, since it is recovered by exponentiating the forecast values in logs, and subtracting the base mean.

Apart from taking logs, no other initial transformations are applied to the data. In several prior works, the data has been smoothed using Gaussian low-band-pass filters on the grounds that eliminating some of the stochastic volatility may more clearly bring out long run causal relationships. This procedure is not used here inasmuch as filtering may fundamentally alter the characteristics of the time series in ways that influence the outcomes of particular tests.

All four series show evidence of both high interannual variability and intermediate-term cycles lasting for periods of up to two decades (e.g., warming from the early 1920s to the mid-1940s, cooling until the early 1950s). Because of this pattern of irregular cycles, there has been some debate as to whether the recorded increase in temperature since the mid-nineteenth century should be viewed as a systematic development or a transitory variation.[3] Sections 3 and 4 are addressed to different elements of this question.

3. Trending behavior in temperature

a. *Deterministic trends and stochastic processes*

The existence of a systematic increase in temperature can be resolved through tests for deterministic trends and degree of integration. The temperature data can be represented as the sum of several components, a constant (α), a deterministic trend (δt), and a detrended stochastic process (X_t):

$$\ln T_t = \alpha + \delta t + X_t. \qquad (1)$$

In monthly temperature data, there will also be a seasonal component; the elimination of the seasonal component in the annual data simplifies the following analysis. The detrended stochastic process can be modeled using the ARIMA (autoregressive integrated moving-average) form:

$$\Phi(L)(1 - L)^d X_t = \Theta(L)\epsilon_t, \qquad (2)$$

where Φ and Θ are polynomials, ϵ_t is a random error, and L is the lag operator. The stochastic process X_t is assumed to have zero mean, because the intercept and

[3] Some authors have argued for instance that the evidence of global warming is sensitive to the benchmark date of the observations, which may introduce a spurious rate of increase into the data (Ellsaesser et al. 1986).

deterministic trend includes the mean of $\ln T_t$. The polynomial on the left-hand side is defined as $\Phi(L) = 1 - \phi_1 L^1 - \phi_2 L^2 - \cdots - \phi_p L^p$, and models the autoregressive (AR) component of the time series, expressing the current value as a function of lagged values. The polynomial on the right-hand side is a moving average (MA) of residuals, defined as $\Theta(L) = 1 + \theta_1 L^1 + \theta_2 L^2 + \cdots + \theta_q L^q$, that is, it is a sum of disturbances.

If for some value d, $(1 - L)^d X_t$ is a stationary process, then X_t is said to be a d-times integrated autoregressive process. When $d \geqslant 0.5$, the process is nonstationary, that is, its variance will increase without bound as a function of time (see Gray et al., 1989; Brockwell and Davis 1991, pp. 274–286).[4]

In this framework, the issue of whether temperature has increased systematically since the mid–nineteenth century can be addressed using two separate tests. The first is for whether temperature contains a deterministic trend; the second is for the degree of integration of the stochastic process. In addition to its relevance to global warming, this has several other implications for practical analysis. To begin with, in regressions involving nonstationary time series, the standard tests of significance (t and F statistics) do not converge to their normal asymptotic distributions. Instead, the normal distributions only obtain when the data is in stationary form. Therefore, in order to ascertain whether exogenous forcing factors are statistically significant in the determination of temperature, the data must be rendered stationary by the appropriate degree of differencing.

b. *Testing for stationarity*

The test for a deterministic trend is a simple regression on time. Since such a regression will almost invariably be autocorrelated, which will bias the t test for significance upward, it is corrected using a maximum-likelihood technique.

The most commonly used test for degree of integration is the Dickey–Fuller (1979, 1981) procedure (hereafter DF), that is, to run a regression of the rate of change on one lag of the level and successive lagged values of the rate of change. The statistic is a t test on the coefficient on the lagged level. Since the true value of the coefficient is not known, this test is normally run against the null hypothesis that it is unity, that is, that the data is integrated of order 1, or $I(1)$. A significant value of the test therefore rejects $I(1)$. The distribution of the t tests in this regression, however, is not standard, but tends toward the negative. The distribution also shifts depending on whether a constant and a deterministic trend are included in the regression; the results from these two specifications are known as the t–τ (trend) and t–μ (no trend) statistics.

Table 1 shows the results of this test applied to the four time series, along with tests for a deterministic trend. In each of the series, the deterministic term is significant. The results of the DF tests are not conclusive. In level form, the t–μ test fails to reject $I(1)$ in all four instances, although the t–τ test rejects $I(1)$ in three cases but only once at the 1% level of significance. This may indicate roots below unity; the DF tests are known to be vulnerable to yielding incorrect findings when there are roots near the unit circle (Schwert 1989).

It is therefore of interest to estimate the degree of integration directly, using the more complex procedure proposed by Geweke and Porter–Hudak (1983, hereafter GPH). The principle is to take the frequency domain representation of the series and regress the periodogram at the harmonic ordinates on the spectral density function. Let X_t denote a time series. The spectral density function, as given in Granger et al. (1980), is

$$F_x(\omega) = (\sigma^2/2\pi)[1 - \exp(-i\omega)]^{-2d} F_e(\omega)$$
$$= (\sigma^2/2\pi)[4 \sin^2(\omega/2)]^{-d} F_e(\omega), \qquad (3a)$$

where F_e is the spectral density function of the error term, ω denotes the harmonic frequencies, j denotes the ordinate, and $[4 \sin^2(\omega_j/2)]$ is the spectral density of X_t. Let $\omega_{Tj} = 2\pi j/T$ denote the harmonic ordinates, and $\beta_x(\omega_{Tj})$ denote the periodogram at the harmonic ordinates. Then, taking logarithms, adding the spectral density function of the error term at frequency zero to both sides and rearranging yields

$$\ln\beta_X(\omega_{Tj}) = \ln[\sigma^2 F(0)/2\pi] - d \ln[4 \sin^2(\omega_{Tj}/2)] + \ln[F_e(\omega_{Tj})/F_e(0)] + \ln[\beta_X(\omega_{Tj})/F_X(\omega_{Tj})]. \qquad (3b)$$

The utility of this formulation is its similarity to a linear regression. The intercept is the term $\ln[\sigma^2 F(0)/2\pi]$ plus the mean of $\ln[\beta_X(\omega_{Tj})/F_X(\omega_{Tj})]$, the disturbance term is $\ln[F_e(\omega_{Tj})/F_e(0)]$, and $-d$ is the slope coefficient. The error term can be constrained to a value of $\pi^2/6$ without loss of efficiency.

The regression coefficient (α_1) can be shown to be an asymptotically consistent estimate of $-d$ if a function $h(T) = T^n$ exists such that as the sample size approaches $h(T)$, the probability limit of $\alpha_1 = -d$.

[4] Stationarity is the property that the covariance between values at any time points is a function only of the distance between these points, not of time itself. Technically, this defines weak stationarity. Strong stationarity requires that, given the distribution function X_t, $F(X_{t+1}, X_{t+2}, \ldots, X_{t+n})$, F does not depend on t for any positive integer n. A further characteristic of stationary series is ergodicity; the correlation through time declines with distance, so that the average through time is an unbiased and consistent estimator of the true population mean.

TABLE 1. Tests for degree of integration.

Test Statistic	East Anglia land and sea	East Anglia land only	IPCC	NCAR
1) Dickey–Fuller tests				
t–τ (level)	−3.21*	−3.41*	−2.91	−3.36***
t–μ (level)	−1.12	−1.29	−1.18	−1.60
t–τ (difference)	−8.18***	−8.01***	−7.87***	−7.95***
t–μ (difference)	−8.18***	−9.01***	−7.87***	−7.95***
2) Geweke–Porter–Hudak test (detrended level)	.66 (.29)	.56 (.28)	.70 (.28)	.69 (.27)
3) Deterministic trend (level)	3.25***	3.14***	2.86***	3.15***
4) Impulse–response function (log difference)	.25	.27	.29	.25

Notes: The Dickey–Fuller tests are run against the null hypothesis of integration of order one [I(1)]. A significant value of the test statistic rejects the null. The Geweke–Porter–Hudak test is for the degree of integration. The figure in parentheses is the standard error of the regression. The test for deterministic trends is a regression on a constant and time. The statistic is a t test on the coefficient on time. The impulse–response function is a frequency domain estimate of the Wold moving-average representation. See Eqs. (5a)–(5d) in the text.
*** Significant: 1% level, ** Significant: 5% level, * Significant: 10% level.

Monte Carlo experiments suggest that the optimal value of n is in the area of 0.5, and this value is used here. The actual regression estimated is

$$\ln(\beta_X(\omega_j) = \alpha_0 - \alpha_1 \ln[4 \sin^2(\omega_j/2)] + \epsilon_t. \quad (3c)$$

The implied degree of integration is equal to $\alpha_1 + 1$.

Table 1 also shows the results of this test, applied to the detrended series. The coefficients range from 0.56 to 0.70. In sum, temperature is well characterized as containing a deterministic trend and a nonstationary stochastic process. These findings strongly reject the possibility that temperature could be stationary for the period in question.

The implication that temperature has increased systematically is, however, subject to one major caveat. The fact that the data sample extends back only to the last century leaves open the possibility that evidence of global warming may be only an intermediate-term phenomenon. Longer-run analysis of temperature has indicated the presence of more extended cycles within recorded history, as well as the higher-amplitude cycles associated with the ice ages. To the degree that the data since the last century does not incorporate these longer-term movements, it may spuriously characterize cyclical changes in temperature as trend-related phenomena.

4. Impulse-response analysis

a. The impulse–response function

A more subtle implication of the finding of $0.5 < d < 1$ in the data is that temperature should be expected to be trend-reverting over time. In general, for such series, the autocorrelation function decays hyperbolically rather than exponentially, implying inertial behavior.

The degree of trend reversion in a time series can be estimated from the impulse–response function. The value of the impulse–response function in the following tests is normalized to lie between 0 and 1. A value of unity means that the time series is permanently raised or lowered by 100% of the value of a disturbance. Values below unity imply partial dissipation of shocks. At 0, perturbations are completely dissipated. Since the relevant substantive issue is whether temperature reverts trend, the impulse–response function is estimated for the actual data ($\ln T_t$) rather than for the detrended series (X_t).

The impulse–response can be quantified using the ARIMA form: $\Phi(L)(1 - L)^d \ln T_t = \Theta(L)\epsilon_t$. The Wold moving-average representation of the ARIMA is obtained by premultiplying by the reciprocal of the AR polynomial, that is, Φ^{-1}. This expresses the time series as the sum of the innovations, filtered by a rational polynomial:

$$(1 - L_t)^d \ln T_t = \Phi^{-1}(L)\Theta(L)\epsilon_t = \Omega(L)\epsilon_t. \quad (4)$$

The Wold moving-average representation can be interpreted as a measure of persistence, inasmuch as by construction it is the ratio of the near-term effect of a disturbance to the long-term effect (Campbell and Mankiw 1987). This representation therefore provides an estimate of the impulse–response function of temperature.

b. Estimation

Several means of estimating the impulse-response function have been proposed. Since the impulse–response is derived from the Wold moving-average representation, it would at first sight appear plausible to estimate it directly from an ARIMA model. Nevertheless, prior studies have in general found this to be unsatisfactory (Christiano and Eichenbaum 1990). The main difficulty involved in drawing inferences from this technique lies with the parameterization of the lag polynomials. The selection criteria frequently used in ARIMA models favor parsimonious specifications; however, low-order polynomials are in general not useful in determining the long-term trend-reverting properties of the data because they accord a higher relative significance to near-term relationships. By definition, the trend-reverting properties of the time series imply dependence on long autocorrelations; low-order models that exclude longer-term relationships will therefore tend to yield biased estimates of the impulse–response function. One way of dealing with this problem, however, is to estimate the Wold moving-average representation in the frequency domain. Technically, this involves multiplying by the z transform in order to obtain the spectral density function. The spectral density integrates over all frequencies (i.e., autocorrelations at all time points); therefore, it does not exhibit the dependence on short-term relationships that is found in time domain models.

The estimation procedure involves the following algorithm. Starting with the Wold moving-average representation, $(1 - L)^d \ln T_t = \Omega(L)\epsilon_t$, the objective is to take the log spectral density of $(1 - L)^d \ln T_t$, mask the nonpositive frequencies to obtain the Fourier transform of the polynomial Λ [see Eq. (5c)], exponentiate it, and obtain the Fourier transform of the rational polynomial Ω. Let z be the information carrying term of the time series. Multiplying both sides by the z transform yields

$$\Omega(z) = \sum_{k=-n}^{n} \Omega_k z^k = \Psi(z)\Psi(z^{-1})\sigma^2, \qquad (5a)$$

where n ranges from negative to positive infinity and Ψ is a polynomial. Evaluating $\Omega(z)$ at the value $z = \exp(-i\omega)$, where ω is the angular frequency, means that the spectral density function of $(1 - L)^d \ln T_t$ can be expressed as a function of the z transform:

$$F_{\ln T}(z) = \Psi(z)\Psi(z^{-1})\sigma^2, \qquad (5b)$$

where F is the spectral density function. Except under special circumstances, $\ln F$ can be expressed as a Laurent expansion:

$$\ln F(z) = \Lambda(z) + \Lambda(z^{-1}) + \Lambda_0 = \sum_{k=-n}^{n} \Omega_k z^k. \qquad (5c)$$

Note that Λ is defined as a one-sided polynomial. Taking antilogs of both sides makes it possible to express the covariance as the Laurent expansion:

$$\Psi(z)\Psi(z^{-1})\sigma^2 = \exp[\Lambda(z)] \exp[\Lambda(z^{-1})] \exp(\Lambda_0), \qquad (5d)$$

which provides an estimate of the Fourier transform of the Wold moving-average representation (Koopmans 1974, pp. 235–241). Note that because temperature is here expressed as a log difference, the impulse-response function is estimated on the percentage rate of change.

Table 1 reports the impulse–response coefficients for both the actual temperature data, which lie in a range of 0.25 to 0.29, implying very little shock persistence. In essence, the effect of stochastic perturbations is resolved as transitory.

This finding disconfirms the hypothesis in Gordon (1991) that the rise in temperature could be a manifestation of random walk behavior. The impulse–response function of a random walk should be unity, that is, any impulse is fully reflected in the future values of the time series.

The evidence of trend-reversion is also consistent with the conventional view of climate as an equilibrium process. In the equilibrium approach the unforced value of temperature is assumed to consist of a random walk around a stable mean. It is because of the presence of continuous forcing that stochastic disturbances are temporary; as short-term variations dissipate, temperature reverts to the path implied by the forcing factors (see Mitchell et al. 1990).

5. Multivariate causal analysis

a. *Causal hypotheses*

The leading causal hypotheses for change in temperature postulate three major forcing mechanisms: atmospheric concentrations of trace gases, solar irradiance, and atmospheric aerosols. The mechanisms underlying the relationship between trace gases and temperature are well understood; they have to do with the radiative trapping properties of CO_2 and to a lesser extent CH_4, nitrogen oxides, and chlorocarbons (for a survey see Watson et al. 1990). There has been less work on solar forcing, due in part to difficulties in measurement; the existing studies differ as to whether ground temperature is influenced by changes in irradiance associated with the solar cycle. The main causal mechanism associated with atmospheric aerosols has to do with backscattering of solar irradiance; this produces heating of the stratosphere but cooling of the troposphere and surface. The differing optical properties of particulates, however, make it difficult to generalize as to their climatic effects. Of the major aerosols, sulfates produced by volcanic eruptions and fossil fuel combustion increase global albedo by scattering sunlight, while elemental carbon works primarily by absorbing radiation.

TABLE 2. Tests for degree of integration: Solar irradiance, atmospheric carbon dioxide and volcanic aerosols.

Test statistic	Solar irradiance	CO_2 (1958–1990)	Volcanic loading
1) Dickey–Fuller tests			
t–τ (level)	−6.05***	−.71	−8.9***
t–μ (level)	−3.86***	−.21	−8.9***
t–τ (difference)	−7.32***	−3.52**	−15.8***
t–μ (difference)	−7.32***	−1.35	−15.8***
2) Geweke–Porter–Hudak test (detrended level)	.33 (.25)	1.47 (.29)	.10 (.27)
3) Tests for deterministic trends (level)	2.35***	4.62***	1.28

Notes: Data on solar irradiance is for 1874–1988. The volcanic loading index is for 1845–1990. The Dickey–Fuller tests are run against the null hypothesis of integration of order one [I(1)]. A significant value of the test statistic rejects the null. The Geweke–Porter–Hudak test is for the degree of integration. The figure in parentheses is the standard error of the regression. The test for deterministic trends is a regression on a constant and time. The statistic is a t test on the coefficient on time. The impulse–response function is a frequency domain estimate of the Wold moving-average representation. See Eqs. (5a)–(5d) in the text.
*** Significant: 1% level, ** Significant: 5% level, * Significant: 10% level.

These mechanisms do not of course exhaust the range of influences on global temperature. Other possible determinants include surface albedo, atmospheric water vapor, and regional emission of waste heat in urbanized areas, but in the absence of adequate data on these causes, their influence can only be measured as a residual.

b. The data

1) CARBON DIOXIDE

The data on atmospheric concentrations of CO_2 begins in 1958 and is here used at an annual frequency (for an analysis, see Keeling 1986; Bacastow et al. 1985). Prior evidence on atmospheric CO_2 has been extrapolated indirectly on the basis of highly incomplete evidence. It is possible to construct series for atmospheric CO_2 back to the 1850s by interpolating from the preindustrial concentration of approximately 275 ppm; the implied growth rate is exp(0.0014). The use of the interpolated trend to proxy for the actual increase in CO_2, however, implies some statistical problems in the ensuing tests. Because the trend is only an approximation of the true stochastic time series, the regressions below are run for two periods, starting in 1958 when the actual CO_2 series is available, and the longer period from 1854 onward using the interpolated data. Nevertheless, as the sequel will demonstrate, the results point to similar conclusions.

The tests for degree of integration of the forcing factors are given in Table 2. The CO_2 data contains a deterministic trend, and the order of integration of the detrended process is 1.47. This is consistent with the finding of upward drift in its rate of change. Data on other trace gases is not available as historical time series, except as interpolations between pre- and postindustrial values. This raises the issue of omitted variable bias, which is dealt with in some studies by extrapolating hypothetical data on other greenhouse gases that are assumed to be correlated with CO_2. If omitted exogenous variables such as industrial trace gas emissions are sufficiently correlated with CO_2, the joint effect should be picked up in the coefficients on CO_2. Conversely, if the omitted exogenous variables are relatively uncorrelated with CO_2, their impact will be picked up primarily in the residuals. Until more data is available on the excluded forcing factors, this issue cannot be resolved.

2) SOLAR IRRADIANCE

While some earlier studies argued that the solar flux is a stationary process with random oscillations around a constant mean (Newkirk 1983), more recent research has supported more systematic variation in irradiance associated with the solar cycle. When solar radiation is integrated over all wavelengths, the increase in irradiance over the 11-year cycle associated with faculae exceeds the decreases associated with sunspots. The relationship between the cycle and irradiance has made it possible to compute a historical series by summing over the solar minimum, the decrease in irradiance associated with sunspot blocking, and the increase in irradiance due to facular brightening (Lean 1989; Foukal and Lean 1990; see also Shine et al. 1990).[5] Esti-

[5] The solar minimum is determined from active cavity radiometer (ACRIM) readings on the Solar Maximum Mission to be 1366.81 W m^{-2}. The decrease in irradiance caused by sunspots is calculated from historical data on the areas and observations of sunspot groups, in conjunction with information about the contrast of sunspots and center-to-limb variation of the sun's irradiance. The effect of facular brightening is determined as a function of several variables, Lyman α (available only after 1975), the 10.7-cm microwave flux (available from 1954 onward), and monthly means of the sunspot number.

mates back to 1874 were obtained by fitting a regression line over the period for which the solar minimum measurements exist (J. Lean, personal communication 1991). The complete series is used at an annual frequency, in logarithmic form.

The series runs only back to 1874; therefore, additional data for 1845–1873 and 1989–90 was calculated using a regression on the sunspot numbers. Both time series were expressed as log levels, and a maximum likelihood correction was used for autocorrelation. In order to capture the full effect of solar cycle, an 11-year distributed lag of sunspots was used. The resulting series back to 1845 exhibits similar cyclical properties to the series for 1874–1988.

As reported in Table 2, there is evidence of a deterministic trend: regression of log solar irradiance on time shows statistical significance at the 2% level. For the detrended series, however, the statistics for degree of integration strongly reject the possibility of nonstationarity.

3) Atmospheric aerosols

The historical time series for volcanic loading is the dust veil index (Kelley and Sear 1982). Because the dust veil is generated by an essentially trendless process, it should be expected to be a stationary series, and this is easily confirmed by the tests in Table 2.

Modeling the effect of other aerosols such as industrially emitted sulfates is difficult both due to lack of historical data and because of collinearity with trace gases. Since the industrial activity that emits sulfur particulates is the same process that gives rise to the greenhouse gases, the damping effects of industrial aerosols on temperature may be impossible to distinguish statistically from the radiative trapping activity of the trace gases, at least over short horizons. As a result, in the regressions estimated here the effect of industrial sulfate emissions, which are excluded from the equation, will be loaded onto the elasticities for CO_2, which are therefore likely to be reduced somewhat from the values implied by the radiative trapping properties of this gas. Over longer horizons, however, the fact that the atmospheric lifetime of sulfates is shorter than that of trace gases may give rise to extreme nonlinearities in the response of temperature, in which the effect of trace gases is temporarily damped until industrial sulfates precipitate.

6. Causality tests

a. Model specification

Specifying structural equations for temperature involves several issues, ranging from the length of transient lags to accounting for omitted exogenous variables.

1) Stationarity

To test for causal significance, the regressions must be estimated in stationary form. The temperature data is rendered stationary by detrending and quasi differencing by the values of d obtained for the detrended series in Table 1. Carbon dioxide is entered as the log first difference of the detrended series for the period from 1958 onward. To run regressions for the full period, however, CO_2 must be entered in log-level form, since it is an interpolated trend until 1958. Nonstationarity means that the results for the full period must be interpreted with caution. It is not necessary to detrend solar irradiance, since the trend in CO_2 detrends the other variables in the regression.

It is important to note here that because dissimilar degrees of differencing are required to achieve stationarity, the regression coefficients will not correctly identify the magnitudes of causal relationships. Instead, the elasticities of response between temperature and forcing factors are estimated from equations in log levels.

2) Lag structures

It is not immediately apparent what restrictions should be placed on the lag structures. In the absence of absorbtion and feedback mechanisms, the effects of solar and CO_2 forcing should be roughly contemporaneous. Interactions between surface reflectivity, reemission of longwave radiation, and thermal absorbtion by clouds and oceans could conceivably generate extended lag distributions. Nevertheless, estimation with distributed lags uses up substantial degrees of freedom, while contributing only marginally to the explanatory power of the equation.

Because CO_2 consists of interpolated data for over a century, a distributed lag procedure is not appropriate. Further, prior studies have established that the effects of volcanic loading are relatively short term. Consequently, it is lagged only one year.

To select lag lengths for solar irradiance, the criterion is a likelihood ratio test, which is based on taking a ratio of the log determinants of the residual covariance matrices of models with different lag structures. The test is defined as: $(T - m_c)[\ln(\det\Sigma_r) - \ln(\det\Sigma_u)]$, where Σ_r is the residual covariance matrix for the restricted model (shorter-lag structure), Σ_u is the residual covariance matrix of the unrestricted model (longer-lag structure), and m_c is a correction factor equal to the number of regressors in each unrestricted model. While the correction factor is not strictly necessary, it improves the small sample properties of the test (Sims 1980). The test statistic has the Chi-square distribution, with degrees of freedom equal to the number of restrictions being tested; in other words, a test for the one-year difference in the lag structure with one equation has a single degree of freedom. The null hypothesis is for the restrictions (shorter-lag structure). A signif-

TABLE 3. Tests for lag length, solar irradiance: Statistics are likelihood ratio test and marginal significance.

Time series	Number of lags (0 = Contemporaneous) 0	1	2	3	4	5
East Anglia, 1845–1990	.42 (.51)	.45 (.48)	.86 (.35)	.36 (.99)	1.16 (.28)	.74 (.38)
East Anglia land only, 1858–1990	.72 (.78)	1.58 (.20)	.44 (.50)	.14 (.70)	.29 (.58)	2.84 (.09)
IPCC, 1856–1990	.61 (.43)	1.69 (.19)	.25 (.61)	1.03 (.30)	2.11 (.14)	1.24 (.26)
NCAR, 1854–1986	.32 (.56)	.40 (.52)	3.51 (.06)	6.67 (.00)	.41 (.52)	.52 (.46)

Notes: The likelihood ratio test is for the difference between the lag length reported and the longer lag structure. The null hypothesis is for the restriction (shorter lag length). A significant value for the statistics rejects the restriction and argues for the longer lag structure.

icant value of the statistic therefore rejects the restrictions and favors the longer-lag length.

Lags of from one to six years are tested for each of the temperature series. The likelihood ratio statistics and marginal significance are reported in Table 3. The tests do not favor extended distributed lags; instead, the effect of irradiance on temperature appears to be adequately captured by the contemporaneous value, and this specification is used in the ensuing regressions.

3) SERIAL CORRELATION

Preliminary estimates of the regressions invariably found evidence of serial correlation in the residuals. The normal solution is to model the disturbance term as a stationary AR(1) process, that is, $\epsilon_t = \rho\epsilon_{t-1} + \eta_t$, where $|\rho| < 1$. The regression is then reestimated in quasi-difference form with the lhs and rhs variables transformed as $Y_t - \rho Y_{t-1}$, where ρ is coefficient of serial correlation. The method of estimating ρ used here is a maximum likelihood search technique.

4) VARIABLE OMISSION

Since serial correlation can be a symptom of the cumulative effects of variables omitted from the regression, it is also worth investigating whether some proxy can be found for the omitted exogenous variables, such as inclusion of a lagged dependent. Here, there is a conflict between theoretical and statistical criteria, inasmuch as the lagged lhs does not in and of itself possess a substantive (as opposed to merely a statistical) interpretation. In this respect, while the lagged lhs can proxy for omitted independent variables, it will also tend to be highly correlated with the included exogenous terms. To ascertain whether the model should contain the lagged lhs, the equations are estimated with and without this term, and the likelihood ratio test is applied. A significant value argues for the inclusion of the lagged lhs.

b. Tests for causal significance

Four basic equations are estimated. Model I is a regression of the log quasi difference of detrended temperature on the log difference of detrended CO_2 (C), the log level of solar irradiance (S), and the level of volcanic loading (V) for the period from 1958 onward:

$$(\ln T_t - d\ln T_{t-1}) = a_0 + a_1(\ln C_t - \ln C_{t-1}) + a_2 \ln S_t + a_3 V_{t-1} + \epsilon_t. \quad (6a)$$

Model II is the same equation with the lagged lhs included. Model III is a regression of the log quasi difference of temperature on CO_2 and irradiance in log levels and volcanic loading for the full period:

$$(\ln T_t - d\ln T_{t-1}) = a_0 + a_1 \ln C_t + a_2 \ln S_t + a_3 V_{t-1} + \epsilon_t. \quad (6b)$$

Model IV adds the lagged lhs. In each equation, volcanic loading is lagged one year. This term is expressed as a level rather than a log-level because it consists primarily of zero values.

The estimated models are shown in Table 4. In both periods, CO_2 forcing is supported at a significance level of 5% or higher. Volcanic loading is periodically significant, particularly for the longer period. The coefficients for solar irradiance all show the correct sign, but are not statistically significant; this finding is not changed by the use of lags. The lagged lhs is not significant for either period, and the likelihood ratio test is well below the range for significance, arguing against including this variable in the regression. In essence, lagged temperature appears to merely proxy for omitted variables and possess no intrinsic interpretation.[6]

[6] As noted earlier, the use of logarithmic data substantially simplifies the estimation of causal relationships that are potentially nonlinear. When regressions of the same form are estimated on the anomaly, in effect restricting the model coefficients to be linear multipliers, the fit of the equations is substantially poorer, indicating misspecification. At the same time, however, it is possible that the "true" model contains further nonlinearities. To test for this possibility, several additional specifications were essayed. First, the loglinear model was reestimated using an iterative maximum likelihood technique. The initial values of the parameters were set using the ordinary least-squares (OLS) estimates, and the algorithm was allowed to iterate until the likelihood function was maximized. The coefficients were in every instance very close to the parameters obtained using OLS with autocorrelation. F-tests did not reject the null hypothesis that the OLS estimates were the true parameters. Another possibility is that the model may be inherently nonlinear, for instance of a form such that the parameters enter as exponentials rather than multiplicative coefficients. Specifications involving multiplicative relationships among the independent variables were also tested. In several instances, the model failed to solve. When it did, the likelihood function was significantly below the loglinear form.

c. Causal magnitudes

The implied causal magnitudes can be obtained from estimating the equations on log levels:

$$\ln T_t = a_0 + a_1 \ln C_t + a_2 \ln S_t + a_3 V_{t-1} + \epsilon_t. \quad (7)$$

The results are shown in Table 5. The coefficients on the log-level series can be interpreted as elasticities of response, technically $\partial T/\partial C$ (or approximately $\ln T_t/\ln C_t$). They express the percentage change in temperature associated with the percentage change in the forcing factors. Since volcanic loading is in level rather than log-level form, the coefficient on this term is only a semi-elasticity.

The elasticity for CO_2 ranges from 0.153 to 0.181 with an average value of 0.165. The implied response of temperature to a doubling of atmospheric CO_2 therefore lies in a range of 2.17° to 2.57°C, with a mean value of 2.34°C.

The elasticities of response to solar irradiance range from 2.91 to 6.67, with a mean value of 5.42. This implies that a 1% increase in irradiance (or 13.67 W m^{-2}) would raise temperature by 0.41° to 0.94°C, with a mean value of 0.77°C. The coefficients on volcanic loading are extremely small, with a mean value of 6×10^{-6}.

Table 6 presents the implied effect on temperature of the change in the exogenous forcing processes over the period for which the regressions are estimated. The effect of CO_2 on global temperature ranges from 0.55° to 0.64°C. The role of solar forcing is extremely small. Based on an increase in irradiance of 0.52 W m^{-2} over the sample period, the implied increase in temperature ranges from 0.017° to 0.038°C. The combined effect of all the forcing factors ranges from 0.58° to 0.65°C.

7. Multivariate impulse–response analysis

In addition to conventional regression analysis, it is useful to examine the impulse–response function of temperature in a multivariate context. This can be estimated from a vector-autoregressive (VAR) model (for a discussion of the VAR technique, see Sims 1980). The VAR is a multivariate autoregression in which every variable in the system is regressed on lagged values of every other variable as well as its own lags. Technically, this is defined as

$$\mathbf{AX}_t - \mathbf{B}(L)\mathbf{X}_{t-i} = \mathbf{u}_t, \quad (8a)$$

where $\mathbf{A}$ and $\mathbf{B}$ are $k \times k$ coefficient matrices, $\mathbf{X}$ is the $k \times t$ matrix of time series, and $\mathbf{u}$ is a $k \times t$ matrix of disturbance terms. The system can be estimated by OLS in the form:

$$\mathbf{X}_t = -\mathbf{A}^{-1}\mathbf{B}(L)\mathbf{X}_{t-i} + \mathbf{A}^{-1}\mathbf{u}_t. \quad (8b)$$

The multivariate impulse–response function is obtained by taking the moving average representation of the entire system. This is defined as

$$\mathbf{X}_t = \mathbf{A}^{-1}[\mathbf{I} - \mathbf{B}(L)]^{-1}\mathbf{u}_t, \quad (8c)$$

where $\mathbf{I}$ is the identity matrix.

Further, let the residual covariance matrix be given by

$$\mathbf{C} = (1/t)\mathbf{v}_t\mathbf{v}_t' = (1/t)\mathbf{A}^{-1}\mathbf{u}_t\mathbf{u}_t'(\mathbf{A}^{-1})'. \quad (8d)$$

To estimate the moving average representation, it is useful to orthogonalize the residuals (make them uncorrelated over time and across equations) by replacing $\mathbf{A}$ by $\mathbf{G}$ and $\mathbf{u}_t$ by $\mathbf{G}^{-1}\mathbf{u}_t$, where $\mathbf{G}$ is a $k \times k$ matrix. The values of $\mathbf{G}$ have the property that $\mathbf{G}^{-1}\mathbf{C}(\mathbf{G}')^{-1} = \mathbf{I}$, and the new residuals $\mathbf{v}_t = \mathbf{G}^{-1}\mathbf{u}_t$ satisfy $\mathbf{E}(\mathbf{v}_t\mathbf{v}_t') = \mathbf{I}$. The standard procedure in the VAR literature is to make $\mathbf{G}$ lower triangular, which corresponds to ranking the variables in their causal priority; the ordering used here was solar irradiance, volcanic loading, CO_2, and temperature. Unless the disturbances are orthogonalized, the resulting analysis will typically not produce meaningful results.

The VARs are estimated for the period 1958–90, using the log levels of the series. To select the lag lengths in the VAR, the likelihood ratio test is applied to the residual covariance matrices of the entire system; for all four series, the test preferred a six-year lag. The results, however, tended to be relatively similar for VARs estimated with different lag lengths.

Table 7 shows the impulse–responses, estimated over a 20-year interval. In each case, the shock is normalized as a one-standard deviation disturbance. Note here that the interpretation of the impulse–response function differs from the univariate case. The multivariate impulse–response analysis captures the effects of innovations in the forcing factors, while self innovations here represents essentially a residual term.

The typical trajectory is one of gradually diminishing irregular oscillations; in every instance, the effects of a shock are partially offset within a few years. Some 12% to 17% of shocks to solar irradiance, 13% to 18% of shocks to CO_2, and 22% to 24% of shocks to volcanic loading are reflected in temperature within two years. The impact of innovations in temperature is even more pronounced, with 64% to 80% of the shock reflected in the level of temperature in the first year. By the third year, however, the effect of the shock has completely dissipated.

The apparent randomness of the impulse–response trajectory after the first few years is notable; the effect of innovations does not converge on a stable value, but rather generates irregular cycles. This finding parallels results obtained from general circulation models, in which temperature is found to exhibit considerable, largely random variation in unforced simulations.

8. Multivariate forecasting models

The log-linear model given in Eq. (7) above can be used to forecast temperature for any desired time ho-

TABLE 4. Tests for causal significance, temperature, and forcing.

rhs variable	Model I 1958–1990	Model II 1958–1990	Model III 1856–1990	Model IV 1856–1990
	Part I: East Anglia, land and sea			
Constant	3.8E-5	3.6E-5	−.72 (−.42)	−.63 (−.31)
CO_2	.08 (2.54)***	.07 (2.56)***	.002 (3.90)***	.002 (3.41)***
Solar irradiance	.184 (0.55)	.151 (.36)	.181 (.75)	.176 (.15)
Lagged lhs	—	−.02 (−1.21)	—	−.05 (−.61)
Volcanic loading	−5E-7 (−1.74)*	−7E-5 (1.40)	−8E-6 (−2.35)***	−8E-6 (−2.36)***
$\bar{R}$-Bar Squ.	.185	.153	.160	.162
SSR	4.1E-5	4.0E-5	3.36-4 3.1E-4	
ρ	−.24 (−1.40)	−.09 (−.26)	−.27 (−3.24)***	−.18 (−1.51)
SE	.0004	.0004	.0005	.0005
Likelihood ratio test	.45 (.50)	—	.17 (.68)	—
	Part II: East Anglia, land only			
Constant	4.7E-5 (.79)	4.1E-5 (.46)	.84 (.44)	.85 (.13)
CO_2	.07 (2.77)***	.07 (3.11)***	.002 (4.05)***	.002 (3.96)***
Solar irradiance	.120 (.91)	.105 (.41)	.141 (.15)	.150 (.47)
Lagged lhs	—	−.05 (−1.80)	—	−.05 (−1.46)
Volcanic loading	−6.1E-5 (−2.15)**	−6.1E-5 (−2.35)**	−6.9E-5 (−2.89)***	6.9E-5 (−2.91)***
$\bar{R}$-Bar Squ.	.271	.215	.195	.186
SSR	4.3E-5	4.2E-5	4.3E-4	4.2E-4
ρ	−.51 (−3.15)	−.37 (−1.25)	−.34 (−3.95)***	−.21 (−2.17)***
SE	.0004	.0004	.0005	.0005
Likelihood ratio test	1.05 (.26)	—	1.61 (.20)	—
	Part III: IPCC data			
Constant	6.8E-5 (.15)	6.1E-5 (.16)	−.20 (−.45)	−.51 (.12)***
CO_2	.07 (2.15)***	.07 (2.46)***	.041 (3.90)***	.002 (3.67)***
Solar irradiance	.366 (.97)	.215 (.31)	.115 (.51)	.091 (.88)***
Lagged lhs	—	−.05 (−1.63)	—	−.113 (−1.35)
Volcanic loading	−8.7E-5 (−2.03)	−8.5E-6 (−1.81)	−.4E-6 (−2.45)***	−4.8E-5 (−2.49)***
$\bar{R}$-Bar Squ.	.454	.418	.145	.140
SSR	5.1E-5	5.0E-5	2.8E-4	2.6E-4
ρ	−.58 (−1.92)*	−.35 (−.16)	−.20 (−2.25)***	−.10 (−.26)
SE	.0004	.0004	.0004	.0004
Likelihood ratio test	.86 (14)	—	.60 (.43)	—
	Part IV: NCAR data			
Constant	4.1E-5 (.27)	3.6E-5 (.22)	−.21 (−.54)	−.35 (−.15)
CO_2	.07 (2.25)***	.07 (2.26)**	.002 (3.61)**	.002 (3.58)***
Solar irradiance	.351 (.46)	.215 (.46)	.186 (.65)	.191 (.39)
Lagged lhs	—	−.06 (−.91)	—	−.085 (−.97)
Volcanic loading	−1E-5 (−2.15)**	−9E-6 (−1.75)*	−4.2E-6 (−2.95)***	4.5E-6 (−2.57)***
$\bar{R}$-Bar Squ.	.278	.275	.168	.170
SSR	4.5E-5	4.2E-5	2.7E-4	2.5E-4
ρ	−.41 (−2.15)***	−.36 (−.46)	−.27 (−2.57)***	−.15 (−.46)
SE	.0004	.0004	.0004	.0003
Likelihood ratio test	.24 (.45)	—	.34 (.54)	—

Notes: Figures in parentheses are t statistics. The likelihood ratio test is for inclusion of the lagged lhs variable. A significant value argues for the inclusion of the lagged lhs. Figures in parentheses after likelihood ratio test are of marginal significance. SSR: sum of squared residuals, SE: standard error, ρ: the coefficient of serial correlation.

*** Significant: 1% level, ** Significant: 5% level, * Significant: 10% level.

TABLE 5. Regressions for the response of temperature to external forcing.

Time series	Constant	Carbon dioxide	Solar irradiance	Volcanic loading	R-Bar Squ.	ρ
East Anglia, 1854–1990	−46.4 (−.95)	.170 (9.29)	6.67 (.98)	−4E-6 (−1.42)	.691	.37 (4.65)
East Anglia land only, 1858–1990	−19.4 (−.33)	.181 (8.52)	2.91 (.36)	−9E-6 (−2.60)	.635	.84 (4.02)
IPCC, 1856–1990	−39.1 (−.77)	.153 (7.59)	5.66 (.81)	−5E-6 (−2.10)	.676	.46 (5.91)
NCAR, 1854–1986	−44.9 (−.83)	.159 (7.57)	6.46 (.87)	−4E-6 (−1.39)	.639	.41 (5.12)

Figures in parentheses are t statistics; ρ is coefficient of serial correlation.

rizon. The first stage in projecting temperature is to compute forecasts for the exogenous forcing factors. A common approach in climatological simulations has been to impose CO_2 growth rates exogenously. This makes it possible to compare the regression equations with previously published model simulations. Prior works (e.g., Hoffert and Flannery 1985) have delineated high, intermediate, and low trajectories for CO_2 corresponding to growth rates of exp(0.0123), exp(0.0069), and exp(0.0039); these values are used to project atmospheric concentrations out to the year 2100. To capture the cyclical properties of solar irradiance it is forecast in two stages. First, the annual sunspot number was projected out to the year 2100 using a spectral model. Second, the previously estimated regression linking irradiance to the sunspot number was used to forecast solar forcing. Finally, because volcanic loading is an unforecastable random series, it is set to zero over the forecast horizon.

The temperature forecasts are reported in Table 8. With low growth in CO_2, the implied increase in the global-mean temperature for the year 2100 lies in a range of 1.28° to 1.55°C. In Part III, where the impact of high CO_2 growth is simulated, the implied increase in global temperature lies in a range of 3.68° to 4.38°C.

It is interesting to compare these scenarios with the results of projecting ΔT from imposed coefficients in a climatological model. The change in equilibrium temperature can be formalized as $\beta_c \ln(CO_{2t}/CO_{2o})$, where $\beta_c = \gamma/\kappa$; γ is obtained from the relationship between absorbed solar flux and outgoing infrared radiation, and κ is a damping parameter (Hoffert and Flannery 1985). The preferred magnitudes of $\gamma = 7.92$ and $\kappa = 2.2$ yield a value of 3.6 for β_c; however, there is some uncertainty associated with the estimate of κ, which may vary over time, yielding a wider parametric range for β_c. Using $\beta_c = 3.6$, the implied increase in temperature for the three CO_2 growth paths is shown in Part 4 of Table 8. This procedure produces slightly higher results than the regression-based forecasts. Specifically, the mean projected values of the anomaly in the year 2100 from the four regressions for the low, high, and medium CO_2 paths are 1.38°C, 2.21°C, and 3.93°C, respectively; these differ from the climatological equation by −0.17°C, −0.54°C, and −0.98°C. These projected values should also be compared with the IPCC (1990) preferred estimates of 1.5°C, 2.5°C, and 4.5°C in 2100 for low, medium, and high rates of CO_2 growth.

There are two plausible explanations for this discrepancy. If the regression-based elasticities for CO_2 are the "true" values for trace gas forcing, the preferred values in the climatological equation must be incorrect, due possibly to underestimation of the offsetting effects of damping mechanisms. Conversely, if the climatological equation captures the true effects of radiative trapping and damping mechanisms, the regression-based elasticities must be interpreted as downwardly biased, possibly the result of failure to capture the implications of the shorter atmospheric lifetime of industrial aerosols. Nevertheless, it is noteworthy that at low rates of CO_2 growth the overall range of the forecast from the climatological and statistical models is of the same general order of magnitude. It is only at extremely high trace gas concentrations that the two approaches yield significantly different forecasts.

9. Conclusions

The statistical techniques used here have yielded several insights into the behavior of global temperature. First, the global temperature increase since the last

TABLE 6. Implied effect of historical forcing on temperature in sample. Temperature increase in degrees Celsius.

Data series	CO_2	Solar irradiance	Volcanic loading	Combined effect
East Anglia, 1854–1990	.608	.038	−.002	.643
East Anglia land only, 1858–1990	.646	.017	−.006	.658
IPCC, 1856–1990	.554	.034	−.003	.585
NCAR, 1854–1986	.562	.033	−.005	.590

TABLE 7. Impulse–responses, VAR estimates. All estimates are for the period from 1958 onward. Statistics are percentage response of LHS to one-standard deviation shock in RHS variable.

	Years of forecast						
Variable RHS	1	2	3	4	5	10	20
			1) East Anglia, land and sea				
Solar forcing	.01	.17	.03	.06	.11	.01	−.01
Carbon dioxide	.15	.09	.01	−.02	.07	.02	.01
Volcanic loading	−.01	−.21	−.02	.02	.01	−.01	.01
Temperature	.67	.29	.09	.06	.011	−.03	.01
			2) East Anglia, land only				
Solar forcing	−.01	.17	.06	−.22	−.01	−.03	.03
Carbon dioxide	.18	.09	.02	−.01	.14	−.08	−.01
Volcanic loading	−.006	−.24	−.18	−.08	.04	.01	.01
Temperature	.80	.27	.06	−.04	.17	.01	.03
			3) IPCC				
Solar forcing	.03	.12	.003	.005	.02	.03	.001
Carbon dioxide	.18	.33	.01	.17	.12	−.01	.01
Volcanic loading	.005	−.22	−.13	−.01	.01	.01	−.01
Temperature	.64	.34	.12	.03	.01	.05	.01
			4) NCAR				
Solar forcing	−.02	.09	.03	.03	.08	−.03	−.01
Carbon dioxide	.13	.03	.03	−.01	.06	.01	−.01
Volcanic loading	−.03	−.22	−.08	.01	−.02	−.01	−.01
Temperature	.71	.31	.09	−.02	.003	.03	.01

Notes: The impulse–response functions are the fraction of a one-standard deviation shock in the independent variable reflected in the forecast error of the dependent variable, at the stated horizon. The impulse–response function is calculated from the moving-average representation of the VAR.

century is a systematic development, as evidenced by the presence of a deterministic trend and nonstationarity in the detrended stochastic process. Second, short-term variations in temperature do not have long-lasting effects on the final realizations of the series; over time, perturbations dissipate and temperature reverts to trend. Third, multivariate tests for causality demonstrate that atmospheric CO_2 is a significant forcing factor. The implied change in temperature with respect to a doubling of atmospheric CO_2 lies in a range of 2.17°C to 2.57°C, with a mean value of 2.34°C. While solar and volcanic forcing are also partially supported, the contributions of solar irradiance and volcanic loading are much smaller. Fourth, in a multivariate system, shocks to forcing factors generate stochastic cycles in temperature comparable to the results from unforced simulations of climatological models. Finally, extrapolation of regression equations predict changes in global temperature that are marginally lower than the results from climatological simulation models.

Several issues touched on only peripherally here may also be tractable using statistical methods. These include whether climatic change should be analyzed primarily using the global mean temperature or through a multivariate signal including regional data, and how to identify the trending component in the temperature data. The next stage in this research will therefore be to estimate the trend in temperature, and ascertain the rate at which actual temperatures converge to the trending component.

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REFERENCES

Bacastow, R. B., C. D. Keeling, and T. P. Whorf, 1985: Seasonal amplitude increases in atmospheric CO_2 concentration and

TABLE 8. Forecasts for temperature anomaly.

Time series	2025	2050	2075	2100
Part I: Low CO_2 growth				
East Anglia, 1854–1990	.61	.88	1.14	1.40
East Anglia land only, 1858–1990	.70	.98	1.27	1.55
IPCC, 1856–1990	.56	.80	1.04	1.28
NCAR, 1854–1986	.56	.81	1.05	1.30
Part II: Medium CO_2 growth				
East Anglia, 1854–1990	.91	1.39	1.84	2.27
East Anglia land only, 1858–1990	1.03	1.54	2.03	2.50
IPCC, 1856–1990	.83	1.26	1.60	1.96
NCAR, 1854–1986	.85	1.30	1.71	2.11
Part III: High CO_2 growth				
East Anglia, 1854–1990	1.45	2.31	3.16	3.98
East Anglia land only, 1858–1990	1.61	2.56	3.48	4.38
IPCC, 1856–1990	1.32	2.10	2.86	3.60
NCAR, 1854–1986	1.39	2.22	2.99	3.75
Part IV: Results from climatic equation				
Low CO_2 growth	.50	.85	1.20	1.55
Medium CO_2 growth	.89	1.51	2.13	2.75
High CO_2 growth	1.52	2.70	3.80	4.91

Notes: Forecasts are computed from equations on log levels. The anomaly is recovered by exponentiation and subtracting the mean. For model elasticities, see Table 5.

Mauna Loa, Hawaii, 1959–82. *J. Geophys. Res.*, **90**(D6), 529–54.

Barnett, T. P., and M. E. Schlesinger, 1987: Detecting changes in global climate induced by greenhouse gases. *J. Geophys. Res.*, **92**, 14 772–14 780.

——, and T. M. L. Wigley, 1990: Detection of the greenhouse effect in the observations. *Climate Change: The IPCC Scientific Assessment*, Cambridge University Press, 239–256.

Brockwell, P. J., and R. A. Davis, 1991: *Time Series Analysis: Theory and Methods*, Springer-Verlag, 577 pp.

Campbell, J. Y., and N. G. Mankiw, 1987: Are output fluctuations transitory. *Quart. J. Econ.*, **102**, 857–880.

Christiano, L. J., and M. Eichenbaum, 1990: Unit roots in real GNP: Do we know, and do we care? Natl. Bur. Econ. Res. Working Paper No. 313, 48 pp.

Crutcher, H. L., and J. M. Maserve, 1970: *Selected Level Heights, Temperatures and Dew Points for the Northern Hemisphere.* NAVAIR Report 50-1C-55, Chief of Naval Operations, Washington, DC.

Dickey, D. A., and W. A. Fuller, 1979: Distribution of the estimators for autoregressive time series with a unit root. *J. Amer. Stat. Assoc.*, **74**, 427–431.

——, and ——, 1981: Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica*, **49**, 1052–1057.

Ellsaesser, H. W., M. C. MacCracken, J. J. Walton, and S. L. Grotch, 1986: Global climatic trends as revealed by the recorded data. *Rev. Geophys.*, **24**, 745–792.

Engle, R., and C. W. J. Granger, 1987: Cointegration and error-correction: Representation, estimation and testing. *Econometrica*, **55**, 251–276.

Folland, C. K., T. R. Karl, and K. Y. A. Vinnikov, 1990: Observed climate variations and change. *Climate Change: The IPCC Scientific Assessment*, Cambridge University Press, 185–238.

Foukal, P., and J. Lean, 1990: An empirical model of total solar irradiance variations between 1874 and 1988. *Science*, **247**, 556–558.

Gates, W. L., 1985: Modeling as a means of studying the climate system. *Projecting the Climatic Effects of Increasing Carbon Dioxide*, M. McCracken, and F. M. Luther, Eds., U.S. Dept. of Energy, 57–80.

Geweke, J., and S. Porter-Hudak, 1983: The estimation and application of long-memory time series models. *J. of Time Ser. Anal.*, **4**, 221–238.

Gilliland, R. L., 1982: Solar, volcanic and CO_2 forcing of recent climatic changes. *Clim. Change*, **4**, 111–131.

Gordon, A. F., 1991: Global warming as a manifestation of a random walk. *J. Climate*, **4**, 589–597.

Granger, C. W. J., and R. Joyeux, 1980: An introduction to long memory time series models and fractional differencing. *J. Time Ser. Anal.*, **1**, 15–29.

Gray, H. L., N. F. Zhang, and W. A. Woodward, 1989: On generalized fractional processes. *J. of Time Ser. Anal.*, **10**, 233–257.

Hansen, J., and S. Lebedeff, 1987: Global trends of measured surface air temperature. *J. Geophys. Res.*, **92**(D11), 13 345–13 372.

——, and ——, 1989: Global surface air temperatures: Update through 1987. Amer. Geophys. Union Paper 7L8065.

——, I. Fung, A. Lacis, D. Rind, S. Lebedeff, R. Ruedy, G. Russell, and P. Stone, 1988: Global climate changes as forecast by Goddard Institute for Space Studies Three-Dimensional Model. *J. Geophys. Res.*, **93**(D8), 9341–9364.

Hoffert, M. I., and B. P. Flannery, 1985: Model projections of the time-dependent response to increased carbon dioxide. *Projecting the Climatic Effects of Increasing Carbon Dioxide*, M. C. McCracken, and F. M. Luther, Eds., U.S. Dept. of Energy, 141–190.

Intergovernmental Panel on Climate Change (IPCC), 1990: *Climate Change: The IPCC Scientific Assessment.* Cambridge University Press, 364.

Jones, P. D., S. C. B. Raper, and T. M. L. Wigley, 1988a: Southern Hemisphere surface air temperature variations, 1851–1984. *J. Climate Appl. Meteor.*, **25**, 1213–1230.

——, ——, R. S. Bradley, H. F. Diaz, P. M. Kelly, and T. M. L. Wigley, 1988b: Northern Hemisphere surface air temperature variations, 1851–1984. *J. Climate Appl. Meteor.*, **25**, 161–179.

——, T. M. L. Wigley, and P. B. Wright, 1990: Global and hemispheric annual temperature variations between 1861 and 1988. NDP-022/R1, Carbon Dioxide Info. Anal. Center, Oak Ridge Natl. Lab., Oak Ridge, Tennessee.

Karl, T. R., 1988: Multi-year fluctuations of temperature and precipitation: The gray area of climate change. *Clim. Change*, **12**, 179–197.

——, and W. E. Riebsame, 1984: The identification of, 10- to 20-year temperature and precipitation fluctuations in the contiguous United States. *J. Clim. Appl. Meteor.*, **24**, 950–966.

Keeling, C. D., 1986: Atmospheric CO_2 concentrations: Mauna Loa Observatory, Hawaii, 1958–1986. Carbon Dioxide Info. Anal. Center, Oak Ridge Natl. Lab., Oak Ridge, Tennessee.

Kelly, P. M., and C. B. Sear, 1982: The formulation of Lamb's dust veil index. *Atmospheric Effects and Potential Climatic Impact of the 1980 Eruptions of Mount St. Helens*, A. Deepak, Ed., Natl. Aeronautics and Space Admin.

Koopmans, L. H., 1974: *The Spectral Analysis of Time Series.* Academic Press, 366 pp.

Lean, J., 1989: Contribution of ultraviolet irradiance variations to the change in the sun's total irradiance. *Science*, **244**, 197–200.

Mandelbrot, B., and J. R. Wallis, 1969: Some long-run properties of geophysical records. *Water Resour. Res.*, **5**, 321–34.

Mitchell, J. F. B., S. Manabe, V. Meleshko, and T. Tokioka, 1990: *Climate Change: The IPCC Scientific Assessment*, Cambridge University Press, 131–172.

Newkirk, G., 1983: Variations in solar luminosity. *Am. Rev. Astron. Astrophys.*, **21**, 429–467.

Schonwiese, C. D., 1991: Multivariate statistical assessments of greenhouse gas induced climatic change and comparison with results from general circulation models. *Greenhouse Gas Induced Climatic Change: A Critical Appraisal of Simulations and Observations,* M. E. Schlesinger, Ed., Elsevier.

Schwert, G. W., 1989: Tests for unit roots: A Monte Carlo investigation. *J. Business Econ. Statistics,* **7,** 147–156.

Shine, K. P., R. G. Dervent, D. J. Wuebbles, and J. J. Morcrette, 1990: Radiative forcing of climate. *Climate Change: The IPCC Scientific Assessment,* Cambridge University Press, 41–68.

Sims, C., 1980: Macroeconomics and reality. *Econometrica,* **48,** 1–49.

Taljaard, J. J., H. van Loon, H. L. Crutcher, and R. L. Jenne, 1969: Climate of the upper air: Southern Hemisphere. Part I: Temperatures, dewpoints, and the heights of selected pressure levels. NAVAIR Report 50-1C-55, Chief of Naval Operations, Washington, DC.

Wang, W.-C., D. Wuebbles, W. Washington, R. Isaacs, and G. Molnar, 1986: Trace gases and other potential perturbations to global climate. *Rev. Geophys.,* **24,** 110–14.

Watson, R. T., H. Rohde, H. Oeschger, and V. Siegenthaler, 1990: Greenhouse gases and aerosols. *Climate Change: The IPCC Scientific Assessment,* Cambridge University Press, 1–42.